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Neural networks have been showing great promise in several areas[1], one of which is the classification of underwater acoustic transients. The classification of low-frequency underwater acoustic transient signals using a neural network based system is investigated. The received acoustic transients are simulated using a time-domain parabolic equation model. The neural network is trained on three source signals and tested by classifying the same signals at 25 different receiver locations in a noise-free, range-dependent (upslope) environment. Overall classification performance is above 90%.

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PERFORMANCE OF NEURAL NETWORKS IN CLASSIFYING ENVIRONMENTALLY DISTORTED TRANSIENT SIGNALS

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Abstract

Neural networks have been showing great promise in several areas[1], one of which is the classification of underwater acoustic transients. The classification of low-frequency underwater acoustic transient signals using a neural network based system is investigated. The received acoustic transients are simulated using a time-domain parabolic equation model. The neural network is trained on three source signals and tested by classifying the same signals at 25 different receiver locations in a noise-free, range-dependent (upslope) environment. Overall classification performance is above 90%.

Synthetic Waveforms and Model Simulations

The synthetic time waveforms which the network is trained on are shown in Figures 1a, b, and c. All signals are linear frequency modulated signals with a center frequency of 50 Hz and identical power spectra (Figure 1d). The signal shown in Figure 1a (class 1) is a 68 to 32 Hz downsweep, Figure 1b (class 2) is a 32 to 68 Hz upsweep and Figure 1c (class 3) is the minimum phase version of the 68 to 32 Hz downsweep.

Environmental distortion of the above signals is simulated in the range-dependent ocean shown in Figure 2 using a time-domain parabolic equation (TDPE) model[2]. The three signals are propagated out to a range of 5 km in 1-km range steps. The signals are received at each range on a 5-element vertical hydrophone array moored to the ocean bottom. The sensor separation is 25 m. The source depth for all three signals is 150 m. This simulation corresponds to the location of a transient experiment conducted about 40 nm off the California coast. Environmental parameters typical of the continental slope in this area are used in the model.
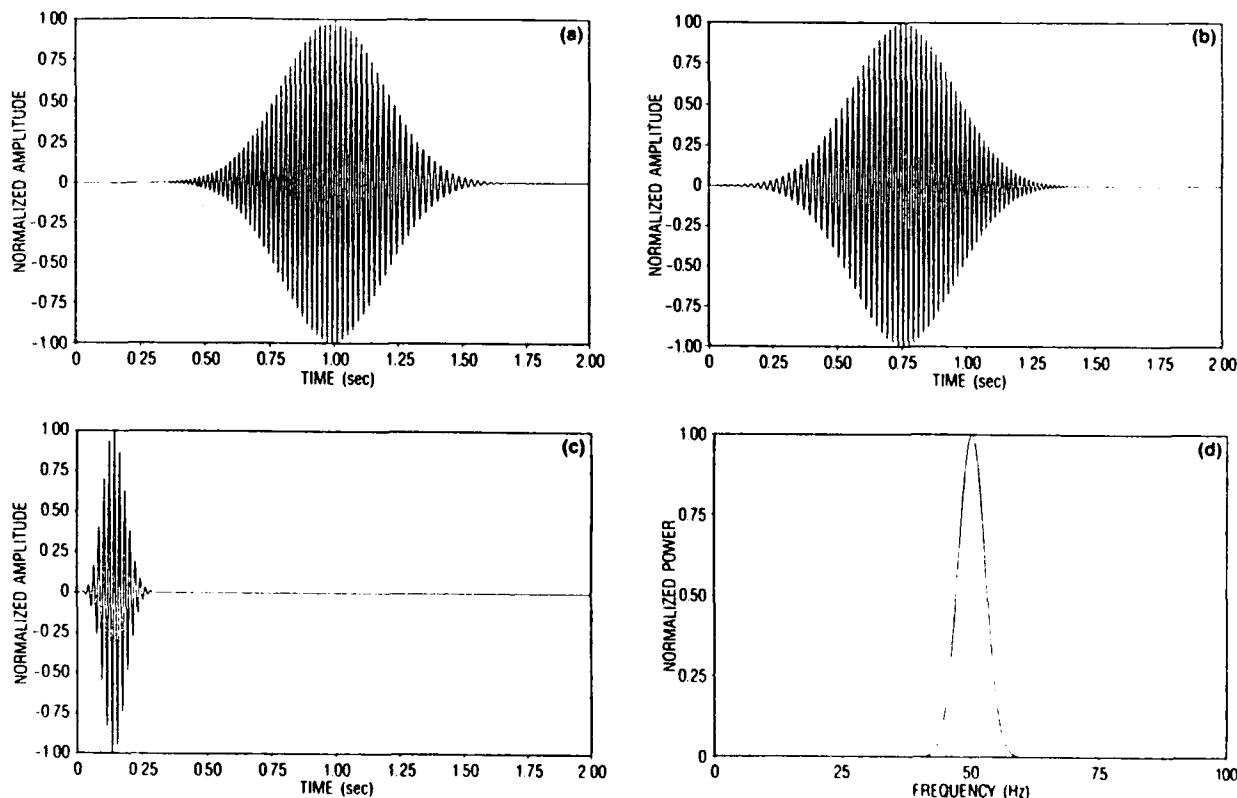

Figure 1. (a) Class 1: Linear FM downsweep 68-32 Hz, normalized time waveform; (b) Class 2: Linear FM upsweep 32-68 Hz, normalized time waveform; (c) Class 3: Minimum phase linear FM downsweep 68-32 Hz, normalized time waveform; and (d) Normalized power spectrum for classes 1, 2, and 3.
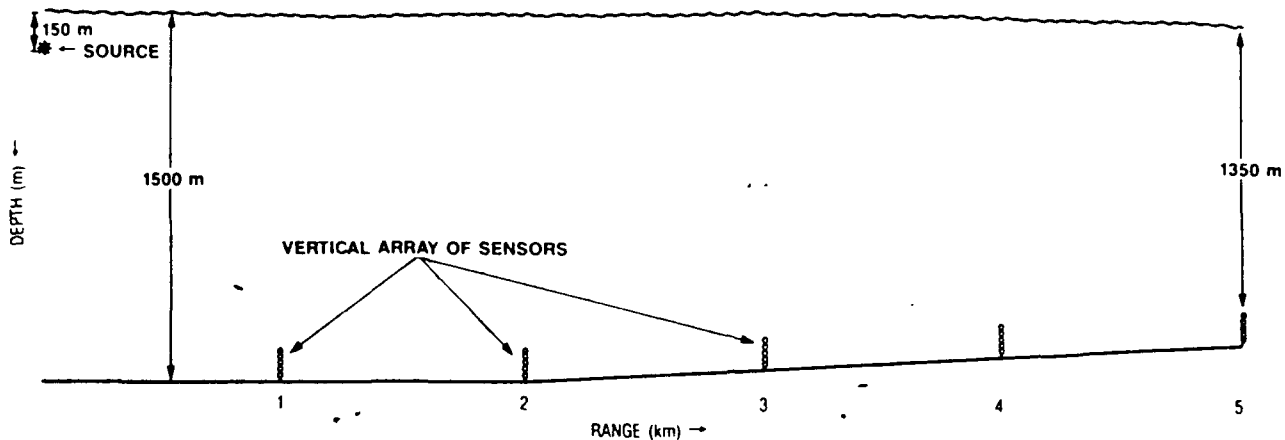
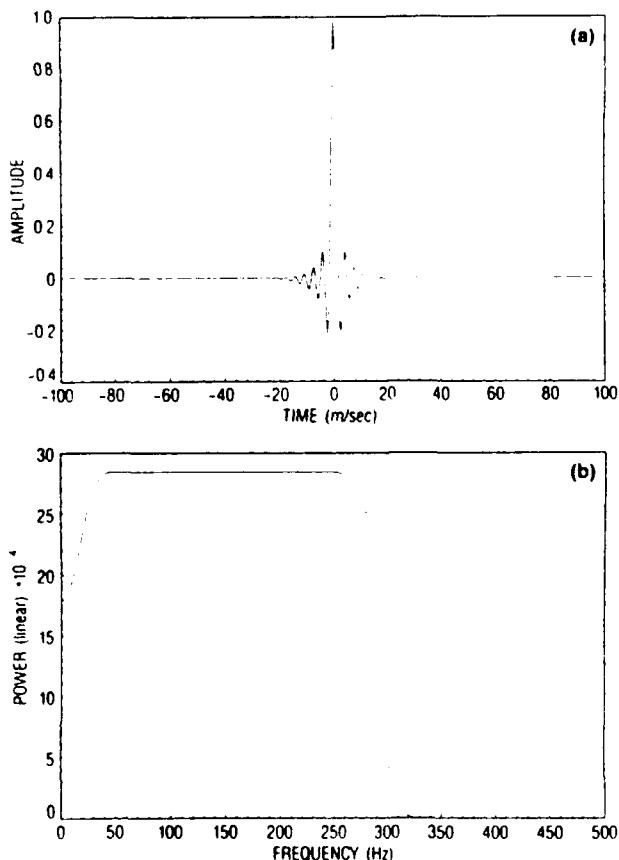Figure 2 Distributed sensor field and range-dependent ocean environment.

Figure 3. (a) TDPE source pulse, and (b) power spectrum of TDPE source pulse.

The broadband pulse shown in Figure 3a is the TDPE source pulse. The power spectrum of this pulse is shown in Figure 3b. The received signals are generated by convolving the propagated broadband pulse with the source waveforms shown in Figures 1a, b, and c. Figures 4a, b, c, d, and e display the pressure field of the broadband pulse as a function of depth and relative arrival time at ranges 1 through 5 km, respectively. Figures 4a through 4e show the bottom depth changing as the pulse marches upslope. The boxes drawn on the ocean bottom represent the array aperture at the

respective range. The array samples the wavefield in depth (given by the height of the box) and in time (given by the width of the box).

At the 1-km range, Figure 4a, there are two fronts, the direct arrival, D, and the surface-reflected arrival, S. At 2 km, Figure 4b, these two arrivals begin to refract back into the water column due to the relatively high sediment sound speed gradient. These refractions are labeled DR and SR for direct-and surface-reflected refractions, respectively. Distortion up to the 2-km range is due solely to the interference between the D and S paths. The bottom depth has not changed up to the 2-km range. At 3 km, Figure 4c, the smeared wavefront trailing the S wavefront consists of the first bottom bounce, B, the refracted fronts DR and SR that have re-entered the water column and the surface-bottom reflected arrival, SB. These fronts have become better separated at 4 km, Figure 4d. Finally, at 5 km, Figure 4e, the above wavefronts are almost fully developed. Signal distortion at each range and depth is due to the mutual interference of these multipaths and the source signal over the aperture of the array.

Neural Network Overview

The most difficult neural networks to build are those that recognize time-varying patterns (spatio-temporal patterns). General Dynamics has been working with neural networks for several years that deal explicitly with the recognition of time-varying signals buried in a great deal of noise[3]. The neural network that was used in these experiments is a product of this work. There are several aspects to the work presented here that are important to point out: (1) the spatio-temporal pattern recognition network is able to learn new spatio-temporal patterns without destroying any of the information concerning the previous spatio-temporal patterns; (2) the neural networks are able to respond very quickly both during training and during recall; and (3) the neural networks are able to generalize quite well.

The neural network used for these experiments is constructed in four parts: (1) feature extraction; (2) spatial pattern classification; (3) spatial pattern to spatio-temporal pattern transformation; and (4) spatio-temporal pattern classification. These four parts are shown in the block diagram in Figure 5.

Several feature extraction techniques were considered including Fourier Transforms, Maximum Entropy Method Coefficients and Gabor Wavelets. We settled on the third transform as it provided an eloquent way of handling the low-frequency data. The transients are passed through a Gabor filter that is 64 sample points in length with an 8 point overlap. Each set of 64 points is called a time slice in this
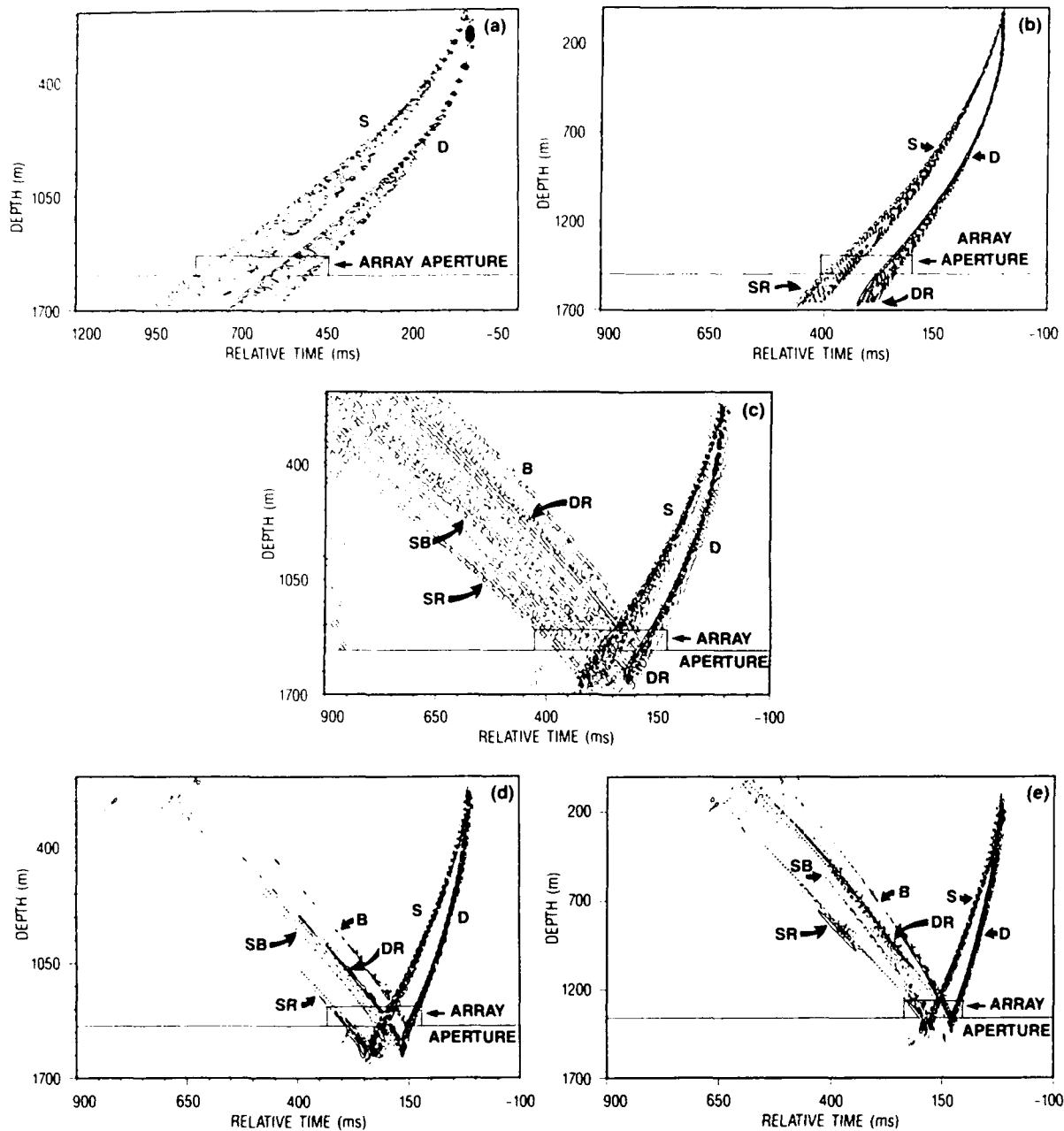
Figure 4. Pressure field for broadband pulse at ranges of (a) 1000 m, (b) 2000 m, (c) 3000 m, (d) 4000 m, and (e) 5000 m.

context. The spectral pattern created from each 64 point sample is 256 bins that represent the frequency range from 0 to 100 Hz. Because it is possible to precompute the coefficients for the Gabor transform filter in advance and place them into a matrix, it is possible to think of the Gabor transformation operation as Linear Associative Memory with hardwired weights. We use the Gabor filter in this context, therefore it is considered to be the first part of this neural network.

The output of the Gabor transformation operation feeds directly to a neural network analog pattern classifier that creates classes of a predefined size from the spectral patterns. The neural network performing the classification is an on-line learning analog pattern classifier entitled the Fuzzy Adaptive Resonance Theory (Fuzzy ART) neural network. Fuzzy ART successfully synergizes the sophisti-

cated adaptive resonance theory (ART) neural network with fuzzy theory to create a flexible, yet robust, pattern classifier that is able to add new pattern classes of a predefined size on-the-fly[4].

The output of the Fuzzy ART neural network is the pattern class of the spectral pattern. By keeping track of which classes that win and when they win, it is possible to create a spatial pattern that represents the spatio-temporal dynamics of the transient signal being presented. The resulting spatial pattern is then fed to a second Fuzzy ART pattern classifier that determines the class for the transient.

Overall, this system has only three parameters that must be tuned and the adjustment for these parameters is very straightforward. Before discussing the results, two points should be made with regards to the neural network studied here. First, this system did not work
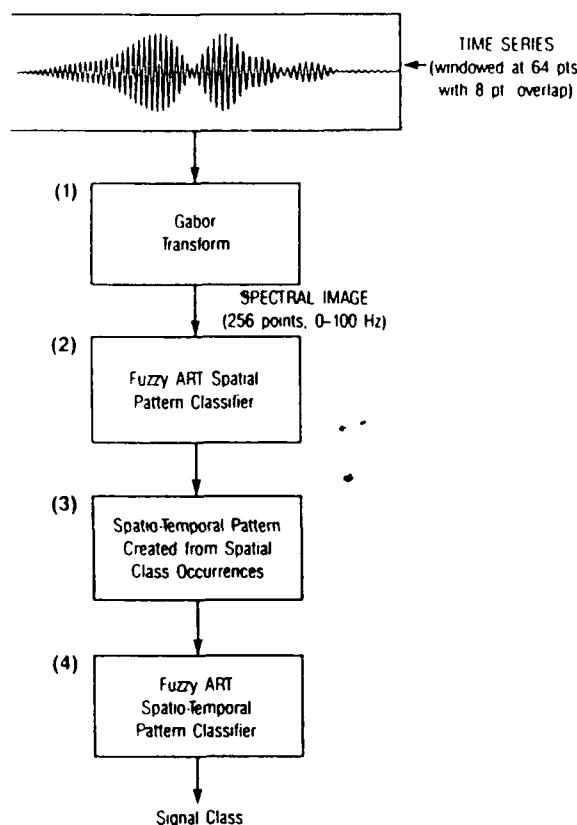
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Figure 5. Block diagram of system.

h noisy data. General Dynamics has created neural network noise cellation techniques that handle noisy data that are not included his design. Second, the transient distortion encountered here is ited to the ranges, depths and environment studied. The results en below would undoubtedly change if these studies were extended ther ranges, depths and environments. The following results are liminary.

Results of Experiments

The neural network is tested in two ways. First, classes 1 and 2 used to train the network. Once these source signals are encoded ' the network. 25 different received signals from each source nal (for a total of 50) are presented to the neural network. Each ceived signal is classified into one of two classes: class 1, wnsweep and class 2, upsweep. Of the fifty received signals, all correctly classified except for one (95% accuracy). Class 2 sweep) is incorrectly classified as class 1 (downsweep) at a range 3 km and a receiver depth of 1425 m. Figures 6a and b show the e waveforms received across the array at the 3-km range. Figure 6a

shows the received waveforms for class 1 (downsweep) and 6b shows the waveforms for class 2 (upsweep). (The top waveforms of Figures 6a, b, c, d, and e are the source signals displayed for reference. The vertical axis is scaled to the absolute maximum amplitude received over the five sensor depths. For example, in Figure 6a, the bottom sensor at 1450-m depth has the largest peak amplitude at this range over the 5-element array. The source signal amplitude is one. There is no significance to location of the signal in time. Therefore, arrival times cannot be inferred from the figures).

The next experiment demonstrates the ability of the neural network to nondestructively add new spatio-temporal patterns by adding a third signal to the neural network. This is the minimum phase signal, class 3, Figure 1c. Like the first two source signals, this signal also has 25 received signals that are used to test the network. The combined test set consists of 75-received signals. 25 from each of the source signals. Out of 75 received signals, only 7 are classified incorrectly. Two of the class 2 signals are classified incorrectly as class 3 signals at the 3-km range for receiver depths of 1400 and 1425 m. Compare Figures 6b, second test, and Figure 6c. Five of the class 1 signals are classified incorrectly as class 3 signals at the 1-km range for all receiver depths. Compare Figures 6d and 6e. All of the class 3 signals were correctly classified. Overall the classification performance was above 90%.

Conclusions

The results presented here are preliminary, but encouraging. With only knowledge of the source signal, the neural network was able to recognize the received signals with 90% accuracy. Although the received signals that were presented to the network were studied under limited environmental conditions (no noise and short range) they were similar in their time-frequency character. This indicates that the approach has the potential of distinguishing desired transients from noise transients. In addition, this technique allows new signals to be added on-the-fly, making this approach to transient signal identification look extremely promising.

Acknowledgments

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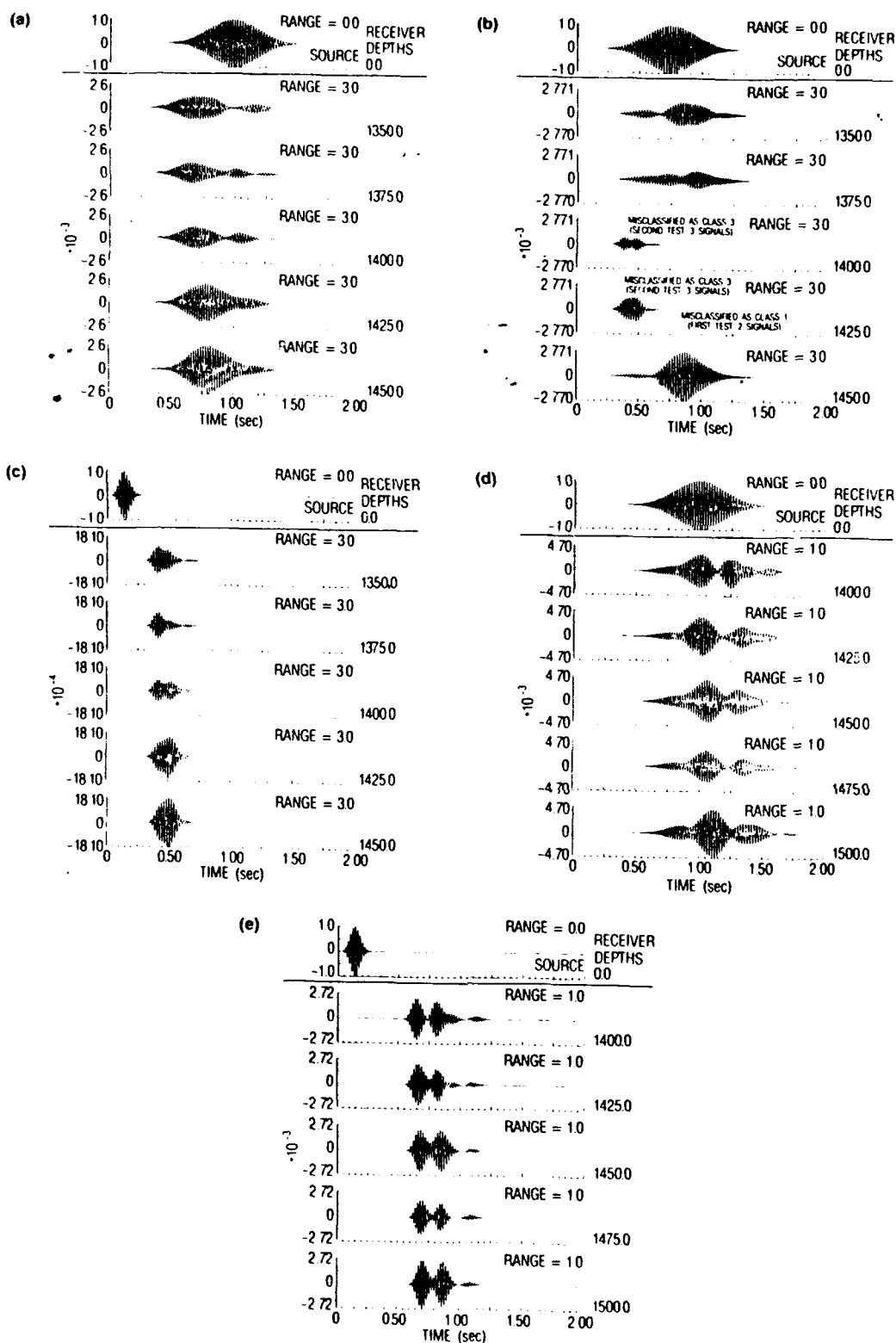4. Simpson, P. (1990). Fuzzy Adaptive Resonance Theory, General Dynamics Technical Memorandum GDE-ISG-PKS-11.

Figure 6. (a) Class 1, downsweep at R = 3 km upslope; (b) Class 2, upsweep at R = 3 km upslope; (c) Class 3, minimum phase downsweep at R = 3 km upslope; (d) Class 1, downsweep at R = 1 km upslope (misclassified all Class 1 as Class 3); and (e) Class 3, minimum phase downsweep at R = 1 km upslope.